Research Article

An Abnormal Signal Processing Method for Sensors Using Convolution Neural Network

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The combination of sensor and neural network (NN) is an important development direction for intelligent sensors. This paper discusses the application of NN in sensor signal processing, introduces the basic principles, and illustrates the application method with examples. Based on the analysis of sensor’s abnormal signal processing, a diagnostic scheme based on CNN is proposed. At each current moment, NN is trained by the latest historical dataset of fixed length to complete the forecast of the next moment. The confidence interval is determined by the model’s residual of NN. Moreover, this paper proposes a signal noise reduction and compression method of multisensor system using the CNN. A multisensor sequence of noisy output signal and target’s true value are used as samples for network training, and the trained network is tested with test samples. The effectiveness of this method is verified by simulation of several typical function approximations. The results strongly suggest the advantages of CNN method for sensor abnormal signal processing and provide a solid foundation for the reliable use of sensors in such type of problems.

1. Introduction

Modern industrial production system has the characteristics of large-scale, complex, continuous, high-speed automation of production equipment [1]. It has significant advantages when it comes to improving productivity, reducing cost, saving energy and manpower, reducing the rejection rate, and ensuring product quality. At the same time, the more complex the system becomes, the higher the probability of failure will be. Sensors play an important role in the control system of engines in industrial production system. Compared with other parts, sensors are more prone to malfunctioning [2]. For highly complex systems, it is far beyond the operator’s ability to quickly and timely detect and identify various faults in the system, which makes automatic fault detection and diagnosis more and more necessary. The fault detection and diagnosis technology is developed with the need of establishing a “monitoring system” [3]. The reliability of the sensors plays an important role in the control and optimal operation of the system. At the same time, their output values act as a base for fault diagnosis of the system. Therefore, it is extremely necessary to study the abnormal signals of the sensors [4]. Each sensor has hysteresis characteristics, which makes them produce more errors. In sensing technology, “hysteresis” means that the sensor gets different outputs with the same input value during the process of increasing and decreasing the input value [5]. When the sensor network is affected by external events, or the sensor nodes themselves have software or hardware failures, the measured data of these nodes will be abnormal. The factors affecting the sensor performance are complex and multifaceted. If the structure size is large and the time response characteristic is poor, input-output characteristics are nonlinear and drift with time. Moreover, various parameters are easily affected by the change of environmental conditions and drift, low signal-to-noise ratio, vulnerable to noise interference, cross sensitivity, low resolution, and so on.

Once the sensor detects the target parameters, the sensor output contains white noise due to the influence of random environmental noise and sensor quality [6]. Moreover, as the structure of the unit becomes complex, there are other parameters and circuits to be monitored [7]. For some
malfunctioning, it is extremely difficult for operators to find the faults and their sources, timely and correctly. Therefore, the performance of sensors in reality is often unsatisfactory and far from the requirements. The fault of the sensor will affect the adjustment of control system, making the system unable to control the engine thrust, accurately and timely [8]. It is necessary to ensure the timely detection of faulty sensor for accurate signal reconstruction. This ensures that the control system can accurately adjust the engine. In some fields, once a certain equipment or a certain part of the control system breaks down during operation, it may cause huge economic losses and even bring disastrous consequences such as endangering the lives of human beings [9]. At present, sensor fault detection methods mainly include hardware redundancy method, expert system method, analytical redundancy method, and NN (neural network) method. Among them, the hardware redundancy method uses more equipment, occupies a large space, and costs a lot [10]. It is difficult to acquire the knowledge of expert method, and it is next to impossible to diagnose the faults. Analytic redundancy method needs an accurate mathematical model, which is quite difficult in practical implementation [11].

Due to the continuous expansion of system scale, increasing complexity and huge system investment, people urgently need to improve the reliability, maintainability, and security of the whole system [12]. Therefore, it is necessary to establish a monitoring system to supervise the automatic running state of the whole system, continuously detect the changes and fault information of the system, and then take necessary measures to prevent the catastrophic circumstances. NN technology is an extremely attractive research field at present [13]. Judging from the fruitful achievements in many applied research fields, the development of NN has great vitality [14]. The reason why NN can show distinctive functions in practical application is that it represents a new method system. This paper introduces the basic principle of CNN technology and its application in abnormal signal processing for sensor technology. NN takes significantly longer time and a lot of system resources in the learning stage, but it is fast in the testing and detection stage, and the resource occupancy rate is low, so it can be used for real-time detection. The major contributions of this paper are as follows.

(1) This paper deeply analyzes the advantages of CNN compared with other NNs, deduces the training algorithm of CNN, and improves the traditional NN training algorithm. We used the normal sensors to predict their signal that may be measured as abnormal by NN. We use the actual output of the sensor and NN output to generate residual error and set the threshold to determine whether there is a fault or not.

(2) To compare and verify the performance of different detection methods, this paper uses MATLAB simulation to conduct various experiments. The results of these experiments show that the detection rate of sensor abnormal signal based on CNN is higher, and the false alarm rate is lower. The network has satisfactory performance, and it is of great significance to improve the sensor abnormal signal processing.

The rest of this paper is as follows. The literature studies are presented in Section 2 followed by proposed methodology in Section 3. The proposed abnormal signal processing for sensors nodes is discussed in Section 4, which is followed by results analysis and discussion in Section 5. Finally, this work concludes in Section 6.

## 2. Related Work

The authors of [15] put forward a method to identify the environmental data stream which obviously deviates from the historical pattern. This method is an autoregressive data-driven model based on data flow and its prediction interval, which has the characteristics of fast execution, large amount of data, and no need to classify outliers in advance. The authors in [16] briefly introduces the technical basis of NN and BPNN (backpropagation neural network). The principle and method of sensor fault diagnosis based on NN observer are discussed. In [17], the authors detected anomalies according to the change of correlation coefficient between predicted traffic sequence and actual traffic sequence of WSNs nodes. Experimental results show the effectiveness of this method. The work of [18] used NN’s multilayer perceptron model, combined with rolling learning-prediction mechanism, to propose a kind of modeling using historical data: a method of estimating current data and detecting outliers according to the difference between the estimated value and the actual measured value. The work in [19] is based on the detailed study of the basic performance of system being diagnosed, and the sensor fault diagnosis of a certain hydraulic system was studied by using NN method. The study of [20] used normal sensors to predict faulty sensors and establishes the spatial model of signal prediction of aero-engine speed sensors. Moreover, in [21], the authors proposed an abnormal data detection algorithm based on the widening histogram. It clusters the dynamic sensing data in the network into a wider histogram by means of data clustering to accurately detect abnormal data while avoiding unnecessary data transmission. The literature of [22] pointed out that the signals of faulty sensors would make the control system make wrong decisions, which would lead to the waste of energy and the decline of indoor air quality. In [23], the authors aimed at the problem of multisensor fault diagnosis, introduced NN into the principal component analysis model, and proposed a multisensor fault diagnosis model based on principal component analysis. In [24], the authors compared and analyzed the characteristics and accuracy of engine model, space model, and time model in signal reconstruction. The results show that the accuracy of time model is higher than that of space model and engine model. In [25], the authors studied the application of wavelet analysis in sensor fault diagnosis and discusses the application of various wavelet basis functions in sensor fault diagnosis in detail.
Based on the previous research, this study completed the research task. This paper summarizes the existing sensor fault diagnosis methods and expounds the advantages and disadvantages of these methods. Aiming at the shortcomings of current sensor abnormal signal processing methods, a sensor abnormal signal processing method based on CNN is proposed. Modular NN with two inputs and one output is used to construct the basic probability distribution function. Each trained network is used as a module separately. When adding new parameters or sensors, it is only necessary to train the newly added network, which does not affect the function of the original module. Moreover, the network training time is short, easy to converge, and has good real-time performance. After the classification network is identified, the result is used as the initial evidence of evidence theory, and then the trust degree of each sensor fault can be obtained through the fusion calculation of evidence combination rules. In order to verify the effectiveness of this method, the algorithm programs of CNN and other networks are designed by MATLAB software, and a large number of simulation experiments verify that this network is superior to other networks in training speed and network performance. This system has a good diagnosis and processing effect for sensor abnormal signals and can meet the real-time and modular requirements of practical applications. The research in this paper has important theoretical significance for sensor abnormal signal processing.

3. Methodology

3.1. Application of NN in Sensing Signal Processing. NN is an information processing model by simulating biological NN. NN is a nonlinear function approximation method without selecting the basis function system [26]. In this paper, CNN’s highly nonlinear description ability is used to realize the processing of sensing signals. Because NN is based on the input-output information of the object, it constantly learns the network parameters to realize the nonlinear mapping from input parameters to output parameters. Adaptive learning can also be carried out according to the new data samples from the mechanism model and the actual running object, and through continuous real-time learning, it can adapt to the slow change of object parameters. Compared with the traditional NN, the structure of CNN has reliable theoretical basis, strong function learning ability and generalization ability, and the trained network has strong anti-interference ability to noise. This method overcomes the difficulties in mechanism modeling. CNN can complete a large number of information processing tasks, and its application involves a wide range of fields.

Some problems need to be considered when designing the sensor abnormal signal processing method based on CNN, such as (1) topology of the network, (2) selection of neuron transformation function, (3) network initialization, and (4) setting of training parameters. Associative memory refers to the realization of pattern perfection and the recovery of mutual memories of related patterns. CNN’s information is distributed and stored in the connection weight coefficient, which makes the network have high fault tolerance and robustness. However, noise interference or partial loss of input pattern often exists in pattern recognition. This feature of the network makes it successfully used in pattern recognition. The NN structure is shown in Figure 1.

As we all know, sensors are tools for acquiring information and signals. At present, the most widely used speed sensors mainly include magnetoresistive, Hall, and magnetoelastic types. Commonly used pressure sensors are vibrating cylinder type, silicon capacitive type, resonant type, etc. Magnetoresistive speed sensor uses the physical magnetoresistance effect of magnetoresistance to apply a certain current to the semiconductor and place it in a magnetic field perpendicular to the current. At this time, the resistance increases and the current decreases. Hall sensor drives Hall element to move in magnetic field according to Hall effect to generate Hall potential. This sensor is a small closed sensor with the advantages of stable performance, low energy consumption, strong anti-interference ability, and wide temperature range. Magnetoelastic speed sensor is widely used in aero-engine.

The application of CNN to sensor signal processing involves two important issues: pattern preprocessing transformation and pattern recognition. Preprocessing refers to accepting a formal pattern and applying NN to transform it into more patterns of desired or available forms. Pattern recognition is the operation of mapping a pattern to other types or categories. Later, when the network inputs relevant information, this memory pattern will be recalled by the network. The modeling of sensor system based on NN includes direct inverse system modeling, forward-inverse system modeling, and inverse-inverse system modeling. The training methods of NN include supervised learning and unsupervised learning. There is an evaluation standard for the output of supervised learning network. The application of NN in sensor signal processing is based on the function approximation ability of NN, and this ability is used to model the sensor. Many literatures have studied the function approximation ability of NN.

3.2. Sensor Fault Diagnosis. With the improvement of automation technology and system complexity, the number and types of sensors used in a system are increasing, and a large number of sensors used for parameter measurement and state control cannot be ignored. Unstable performance of the sensor or errors in installation operation will often lead to failures, which will lead to false monitoring signals, and the consequences will be very serious. Sensor fault diagnosis technology is a comprehensive technology, which involves many disciplines, such as modern control theory, signal processing, computer engineering, NN, and applied mathematics. On the basis of these theories, many methods of sensor fault detection and diagnosis have been formed. There are many reasons for sensor failures, and different types of sensors will have different types of failures due to their different placement positions and their own structural differences. The faults of sensors are generally divided into “hard fault” and “soft fault.” “Hard fault” refers to sudden damage or complete failure, and this kind of sensor fault is
easy to identify. "Soft fault" refers to some slow changes, such as offset, drift, or calibration coefficient deviation, which are relatively difficult to solve. Generally speaking, the fault reasons of speed sensor may include (1) short circuit, open circuit, and weak connection of wires; (2) the original part of the speed sensor fails; and (3) the signal generating gear may be incorrectly installed. The causes of pressure sensor failure may include (1) pitot tube which is wet or corroded by pollutants, (2) internal rupture of pitot tube caused by strong airflow, and (3) damage of electroplating materials caused by excessive corrosion.

Sensor redundancy is a direct and hardware method. It uses more than three sensors to detect the same point and then determines its correct value by voting or installs more sensors than needed in the system to check each other. With the continuous development of technology, the sensor redundancy method can no longer meet the requirements of sensor fault detection in test system, especially for nonlinear systems that are often encountered in practice. This method uses a lot of equipment, occupies a large space, and is uneconomical. Therefore, people began to apply NN and fuzzy recognition in this field. These two methods can approximate the dynamic model of nonlinear system to deal with the problem of fault detection and have great advantages in practical application. The flow chart of CNN-based sensor network abnormal signal detection method is shown in Figure 2.

The goal of sensor diagnosis is to first find and separate the faulty sensor as early as possible and then carry out other corresponding processing. At present, there is relatively little research on signal reconstruction. Traditionally, there are two research directions. The first one is to use Kalman filter to reconstruct the signal from the fault sensor. The second is the reconstruction of engine model. It is the development direction in recent years to apply intelligent methods to traditional model-based fault diagnosis. At the same time, the hybrid diagnosis system which combines many different intelligent technologies is a development trend of intelligent sensor fault diagnosis research.

4. Sensor Abnormal Signal Processing Method

With the development of artificial intelligence technology, fault diagnosis technology has entered the intelligent diagnosis stage, which makes the diagnosis technology enter a brand new development stage. Various sensors are widely used in nonelectric quantity measurement technology, which are used to convert nonelectric quantity into electric quantity. The output characteristics of most sensors are nonlinear, because their conversion principle is nonlinear. NN fault detection and diagnosis system uses distributed storage information, uses the topology and weight distribution of network to realize nonlinear mapping, and uses global parallel processing to realize nonlinear information transformation from input space to output space. When modeling, we do not need to know the specific characteristics of the parameters, we do not need to build an accurate parameter model, and we only need to sort out and transform the input and output of the research object, so as to realize the fault diagnosis with good real-time performance and high precision.

Three methods are often used in traditional analog indicating instruments. They are as follows: (1) narrow the measuring range and take the approximate value. (2) Adopt nonlinear indicating scale. (3) Add nonlinear correction link. However, with the continuous expansion of measurement range and the increasing requirement of measurement accuracy, these methods may lose their use value. At this time, it can be corrected by NN. Firstly, the sensor data stream is imported, and then it is normalized and the confidence interval is solved. Then, the processed sample data is divided as required to generate training set and test set. After CNN is established, the divided sample data are trained by
network. Finally, it is judged whether the data stream falls within the confidence interval.

The output of the concentration sensor is regarded as the input $y$ of NN, and the concentration value $x$ to be measured is regarded as the output of NN. Train the NN until the mean square value of the estimated error of the output value of NN is small enough, and the learning process will end. Consider the case that only one sensor fails in one sampling period. It is assumed that the $i$th sensor fails at time $k$. At this time, the input of the main network is the output value of each sensor before the failure, that is, the normal signal, so the estimated value of each sensor output by the main network is also the correct signal. Assuming that other parts of the control system are in normal state, we think that at least one sensor has failed, which is called detection rule. However, in the case of only one redundancy, no matter what method we adopt, it is impossible to accurately separate the faulty sensor only based on the data itself. When monitoring, controlling, and optimizing the production process, it is based on some measured values of process variables. Therefore, obtaining reliable, accurate, and consistent estimated values of process variables from measurement data is very important for production process.

The guiding idea of network learning rule derivation is to correct the network connection weights and thresholds according to the errors, so that the errors will decrease along the gradient direction. Within the hidden layer, the output of an $i$th neuron is computed as follows.

$$ y_i = f\left(\sum_{j=1}^{N} w_{ij} s_j - \theta_i\right) = f(\text{net}_i), \quad (1) $$

where $w_{ij}$ denotes connection weight between an $i$th neuron within a hidden layer and the $j$th neuron of the input layer. Moreover, $S_j$ denotes the input of $j$th neuron of the input layer. Lastly, the threshold of $i$th neuron is represented as $\theta_i$. In an output layer, the output of neurons can be computed as follows.

$$ O = f\left(\sum_{j=1}^{P} T_{1j} y_i - \theta\right) = f(\text{net}_o). \quad (2) $$

In this formula, the connection weight between the neurons of output layer and an $i$th layer of a hidden layer is represented by $T_{1i}$. Likewise, the neuron’s threshold value is denoted as $\theta$, and the output error is computed as follows.

$$ E = \frac{1}{2} (t - O)^2 = \frac{1}{2} \left(t - f\left(\sum_{j=1}^{P} T_{1j} f\left(\sum_{j=1}^{N} w_{ij} s_j - \theta\right) - \theta\right)\right)^2. \quad (3) $$

In the above formula, the expected output is denoted by $t$. To calculate the transfer function, a unipolar sigmoid function, the following formula is used.

$$ f(x) = \frac{1}{1 + e^{-x}}. \quad (4) $$

In the formula, $f(x)$ has the characteristics of continuous and derivation and has

$$ f'(x) = f(x)[1 - f(x)]. \quad (5) $$

According to application needs, bipolar sigmoid function can also be used:

$$ f(x) = \frac{1 - e^{-x}}{1 + e^{-x}}. \quad (6) $$

The NN prediction model is established by using the output signal of a single sensor, and then the difference

![Figure 2: Flow chart of sensor network abnormal signal detection.](image-url)
between the predicted output of the sensor and the actual output of the prediction model is used to judge whether the sensor fails. The algorithm in this paper does not rely on optimization ideas such as gradient descent but uses the method of system identification to identify all state parameters. Its convergence speed and accuracy are significantly higher than those of gradient descent algorithms, and it is easy to generalize and implement. When the sensor system is detected to be faulty, in order to eliminate the fault in time, the fault source must be accurately found. In sensor fault diagnosis, it is necessary to clarify which sensor is faulty so that the sensor can be isolated in time, and at the same time, the predicted value of the model is used to replace the normal value of the sensor to ensure the normal operation of the system and realize fault-tolerant control.

Filtering and denoising are basic operations in sensory information processing. In the adaptive noise removal, the whole adaptive noise removal system is divided into two channels: the main channel and the reference channel. In the judgment of system failure and sensor failure description, in view of the fact that the system failure often causes the output of many sensors to deviate from the normal value, the probability of simultaneous failure of multiple sensors in a sampling period is very small. Therefore, if the main network and a certain subnet alarm at the same time, it is considered that the sensor is faulty. If the main network and multiple subnets alarm at the same time, it is considered to be a system failure. The mainnet error is defined as

\[ \text{Mainerr} = \sum_{1}^{\text{Num.Output}} (o_i - y_i)^2. \]  

(7)

The output of the ith subnet is the estimated value of the ith sensor at time k. The error defining the subnet is

\[ \text{Dnnerr}(i) = (o_{di} - y_i)^2. \]  

(8)

In the fault diagnosis system, due to the complexity of the equipment itself, the randomness in the operation process, the instability of the operating environment, the system noise, and the uncertainty of the sensor accuracy reflected in the equipment system information.

The input of the detection system is the superposition of the broadband noise \(x_k\) and the weak signal \(S_k\) to be extracted. Take the expected value \(m_x\) of the background noise as the expected response \(d_k\), namely:

\[ d_k = E(x_k) = m_x. \]  

(9)

Assuming that the background noise is stationary, \(m_x\) can be approximated by a time average. It is assumed that before the weak signal appears, the network learning process has ended; that is, the expected value of the network connection weight matrix has converged to the optimal weight vector \(W^*_x\) determined by the background noise. So there is an offset weight vector:

\[ V_k = W_k - W^*_x. \]  

(10)

where \(V_k\) is the weight offset and \(W_k\) is the weight vector containing background noise and weak signals.

According to the data obtained by the test bench, due to the existence of noise and other interference, the experimental data is dithered in some stable states. In order to improve the accuracy, preprocessing the experimental data is the basic operation. In the engineering fields such as target tracking and multitarget detection, the problem of extracting weak signals from strong background noise is involved. The method based on NN structure and algorithm can extract weak useful signals from broadband background noise. This method extracts weak signals in the network node connection weight vector domain, thus fundamentally solving the problem of frequency selection of extracted signals.

Data fusion is to analyze and combine the data and information from multiple sensors into a comprehensive intelligence according to established rules and, on this basis, provide users with the required information. By standardizing, formatting, sequencing, batch processing, and compressing the input data in advance, the subsequent estimation and the requirements of the processor on the amount and order of calculation can be met. The basic purpose of fusion is that through combination, more information can be obtained than from any single input data element.

5. Result Analysis and Discussion

NN can be widely used, not only because of its good learning and training effect, but also because of its good network generalization ability. The generalization ability of NN means that the trained NN can still give appropriate output for the input values of nonsample set. In this paper, CNN toolbox, BPNN toolbox, and wavelet NN toolbox in MATLAB software are used to simulate and analyze the proposed abnormal data detection method of sensor networks. The experimental data is from a sensor network experimental system in a certain place, and the sampling frequency of this system is once every 20 minutes. 1000 temperature data were selected as experimental data samples. Three-layer NN is selected for training, and sigmoid-type function is selected for hidden layer activation function. Considering the large output range of the actual system, the linear function is selected as the activation function of the output layer. Because the square wave is representative, the square wave input at the normal operating frequency of the system is selected.

We simulate the occurrence of bias fault by adding a random small signal to the original sensor output signal. The output curve of NN after training in this paper is smooth and has no noise interference, so NN has a strong ability to suppress noise. The MSE (mean square error) of different networks is shown in Figure 3.

It can be seen that the MSE of the network is larger at the initial stage. With the continuous training of NN, the network gradually converges, and the MSE gradually decreases until it reaches a certain stable state. Compared with other networks, the MSE of CNN is smaller.

The measured parameters of the sensor reflect the state of the production process and equipment, and there must
be an internal connection between the signals, which reflects the correlation between the parameters. The main factors that dominate the correlation between these variables are the principles of mass balance and energy balance observed in the production process. By calculating the correlation between variables, the process variables are grouped into several correlation vector groups. Generally, sensors have cross sensitivity, which is manifested in that the output value of sensors is not only determined by a constant. When other parameters change, the output value will also change. Divide 1000 data collected by temperature sensors, among which 700 data are used for the establishment and training of NN, and 300 data are used to verify the established NN. Before data analysis, it is necessary to normalize the sample data. Figure 4 is the curve of training error when different NN trains 100 times.

It can be seen that after 100 times of training, the training error of each network changes regularly. From the comparison of convergence speed and accuracy, the training effect of this network is ideal. Through the simulation of NN, the signal prediction of sensor network based on CNN is drawn, and the result is shown in Figure 5.

It can be found that the signal prediction effect of sensor network based on CNN is ideal, and it is in line with the general change trend of original data as a whole.

Use the trained CNN to diagnose the fault data samples. In general, the output values of temperature, humidity, pressure, and other sensors are not in one-to-one correspondence due to different degrees of delay and lag. At the same time, the sensors are often affected by various noises at the work site, so their output values cannot truly reflect the real-time values at a certain point in time. In practical application, due to various restrictions and constraints, it is difficult to obtain complete information between sensors, and often an incomplete relationship is obtained. The operation of this case can be simplified to an extreme case, that is, reducing the number of information sources. Figure 6 depicts the error curves of sensor network signal prediction for different networks.

It is not difficult to find out from the figure that the error curve of CNN-based sensor network prediction has the smallest fluctuation and the average error is small. The average error of the other two networks is larger.

Because the selection of training samples must be representative, it should include all the actual operating conditions of the system as much as possible, including at least all typical operating conditions. NN is based on the statistical distribution probability of samples in events to train and predict the network. Normalization is also to speed up the training speed of NN and the convergence of the network. In the experiment, the absolute value of residual error is compared with the set threshold, and the variance changes to 1. At this time, most of the residual values exceed the alarm threshold, while some of them do not, which is volatile. This is mainly because this kind of fault is similar to free noise and random.

Some data are extracted from the data samples, and the trained CNN, BPNN, and wavelet NN are simulated. The simulation results are shown in Figure 7.

From the actual simulation results, it can be seen that for the trained networks, the network is simulated with the same sample data, and the predicted values of the network in this paper are basically consistent with the actual sample values. For BPNN and wavelet NN, the predicted values of other samples are basically consistent with the actual values, except for a few samples with a larger deviation. Therefore, all three networks have good generalization ability, and the generalization ability of this network is better than other networks.

Many sensor signals often encountered in engineering technology are complex transient signals. Generally, they can be decomposed into the superposition of slowly varying low frequency and transient high frequency parts in both time domain and frequency domain, which requires
bandpass filter banks with different central frequencies and lowpass filter banks with different bandwidths to process signals. Because the fault with reduced accuracy level is similar to free noise, which is random and fluctuating, even if the variance changes greatly, the residual value of some data cannot exceed the alarm threshold. And this part of the data is random. We can get a residual vector by comparing the output when the system fails with the output of NN observer. After filtering, the residual vector can be used to judge the occurrence of fault. At this time, setting a certain threshold can be used for fault alarm. The advantage of this method is that it is fast and accurate.

The experimental data used in this paper are collected when the system is running normally and the load change is relatively stable. The transient process of the system is relatively short, mainly running under relatively stable conditions. Therefore, this method has a wide application range. Experiments show that it is feasible to use this method for fault detection. It can complete the sensor fault detection task under the condition that the variance mutation of the input signal and the sensor mutation exist simultaneously. It lays a foundation for further fault isolation, signal self-correction, and other processing. Moreover, the NN of this paper has stronger learning ability.
and higher approximation accuracy and simpler network structure and faster convergence speed.

6. Conclusions

The key of abnormal signal processing is how to form a feature outline of normal activities of users or systems. NN caters to the characteristics of sensing information and can complete the complex mapping from input mode to output mode. Therefore, the combination of sensor and NN is inevitable development of technology. The self-study habit and adaptability of NN attract more and more scholars to study how to apply it to abnormal signal detection. It mainly trains a large number of samples and constantly learns and adjusts the feature pattern of the subject, so as to construct a feature contour with adaptability. Compared with the traditional
NN, CNN can avoid the blindness of the traditional NN in structural design and has strong function learning ability and popularization ability. In this paper, CNN is used to solve the problem of sensor abnormal signal processing. The diagnosis of slow-changing fault of sensor under normal working frequency and extreme working frequency is studied. The diagnostic results show that under different conditions, this method can quickly and accurately determine the time, location, size, and type of sensor failure. At the same time, the diagnosis method is robust. Through simulation analysis and simulation experiments, it is proved that this network has strong fault diagnosis ability. In addition, the detection method in this paper has the characteristics of high sensitivity, low requirements for input signals, and no need of sensor mathematical model. The principle and method of applying CNN to abnormal signal processing of sensors provided in this paper plays an important role in improving the performance of sensors and tapping the potential of sensors. With the continuous enrichment of fault knowledge, the network can also continuously improve the diagnostic accuracy through learning. The research has achieved some conclusions, but there are still some shortcomings. Follow-up work can study and analyze the use of other optimization algorithms to adapt to the development of optimization algorithms.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

We declare that there is no conflict of interest for publication of this paper.

References


